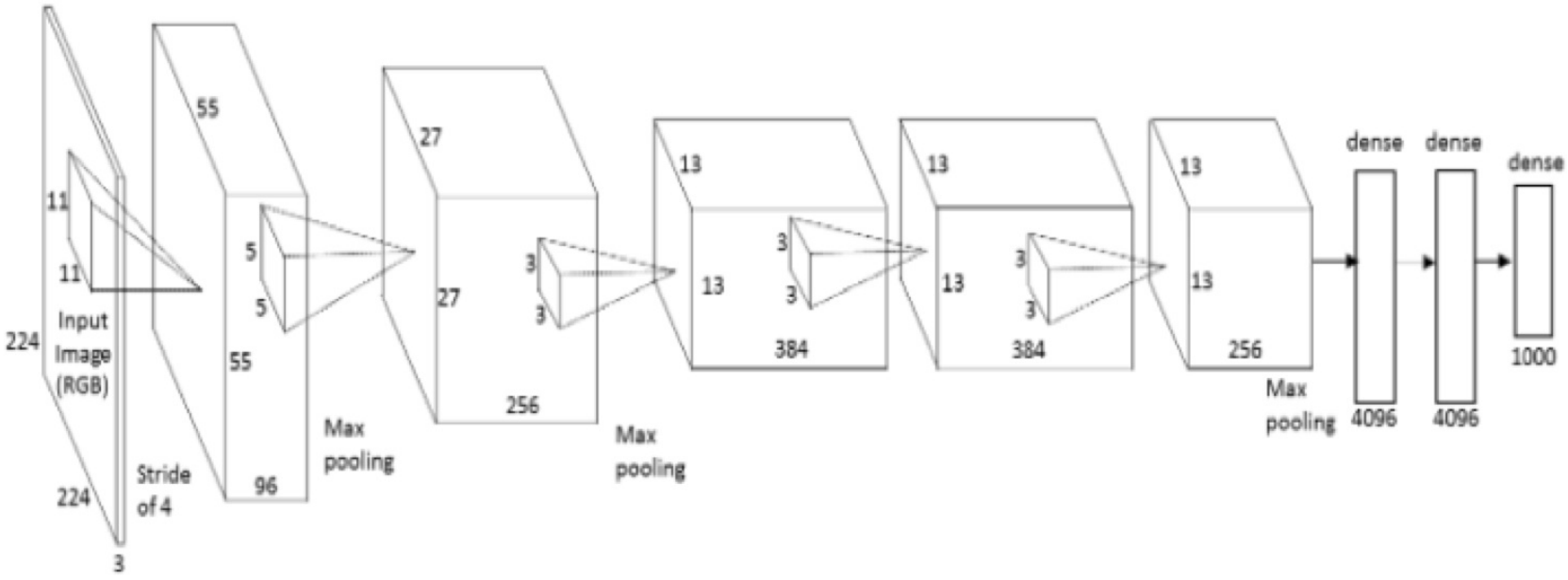
Lesson 8

- Examples of real CNNs
- Transfer Learning

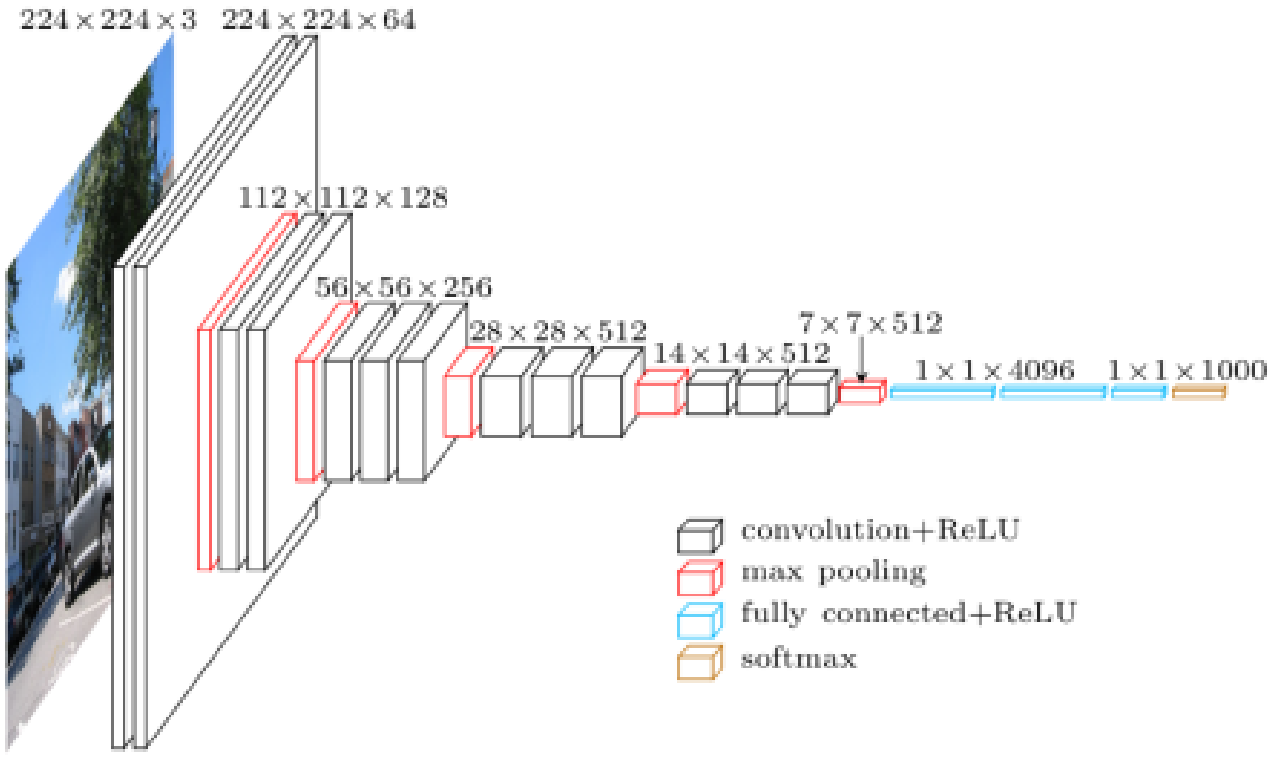
AlexNet

AlexNet Architecture (Krizhevsky, Sutskever e Hinton), winner of a NIPS contest in 2012.



VGG

VGG 16 (Simonyan e Zisserman). 92.7 accuracy (top-5) in ImageNet (14 millions images, 1000 categories).



Picture by Davi Frossard: VGG in TensorFlow

Inception V3

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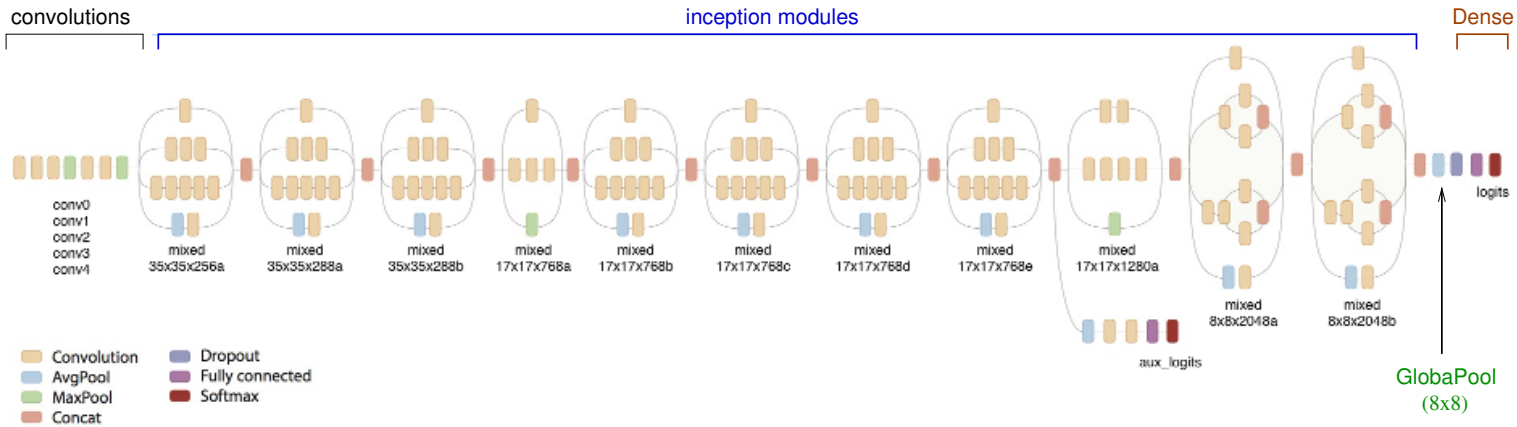
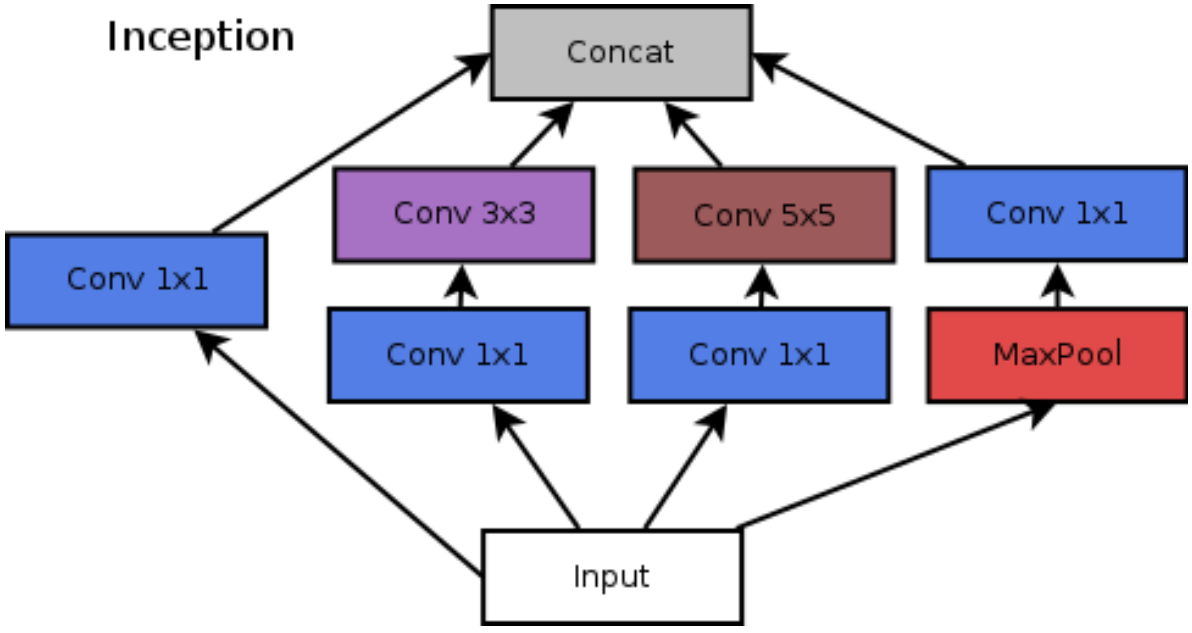


The convolutional part is a long composition of

inception modules

Inception modules

The networks is composed of inception modules (towers of nets):

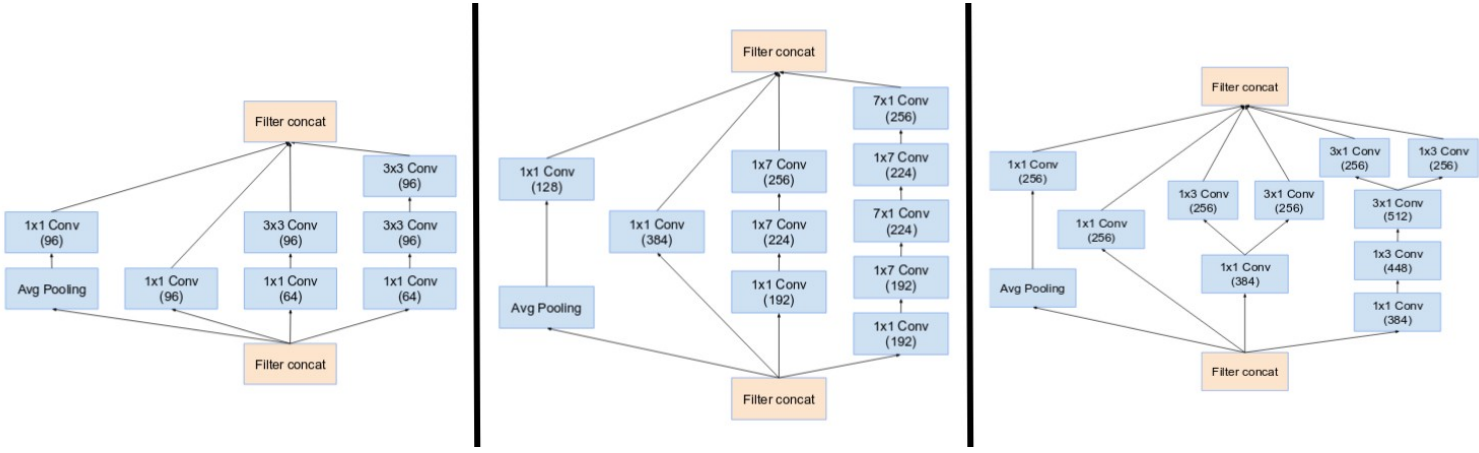


Video from the Udacity course "Deep Learning"

Variants

The point is to induce the net to learn different filters.

Many variants proposed and used over years:



The inception hypothesis

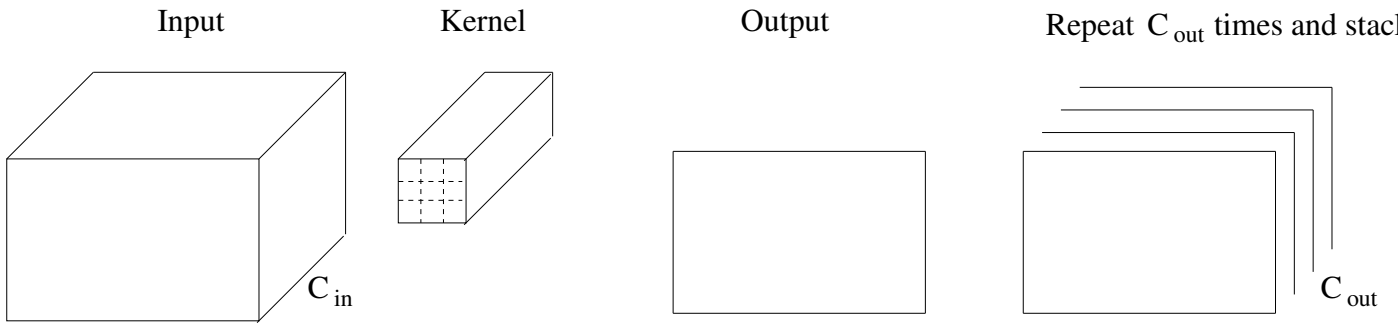
Remember that normal convolutional kernels are 3D, simultaneously mapping cross-channel correlations and spatial correlations.

It can be better to decouple them, independently looking for cross-channel correlations (via 1×1 convolutions), and spatial 2D convolutions.

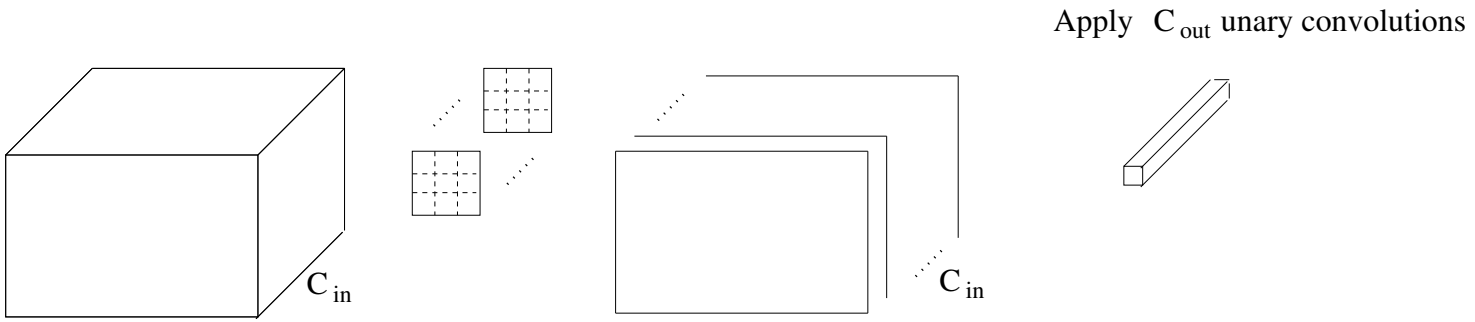
Inception modules can be understood as an intermediate step between a regular convolution and a depthwise separable convolution (a depthwise convolution followed by a pointwise convolution).

Depthwise separable convolutions

Traditional Convolutions



Depthwise Separable Convolutions



Depthwise separable convolutions

Suppose we have a convolutional layer with a 3×3 kernel, 16 input channels and 32 output channels. The input is convolved 32 times with different kernels of dimension $3 \times 3 \times 16 = 144$: we have a total of $32 \times 144 = 4608$ parameters.

In a **depthwise separable convolution** on the same example, we first traverse the 16 channels with a different 3x3 kernel, and then we apply 32 different kernels with dimension $1 \times 1 \times 16$. The total number of parameters is $16 \times 3 \times 3 + 32 \times 1 \times 1 \times 16 = 656$.

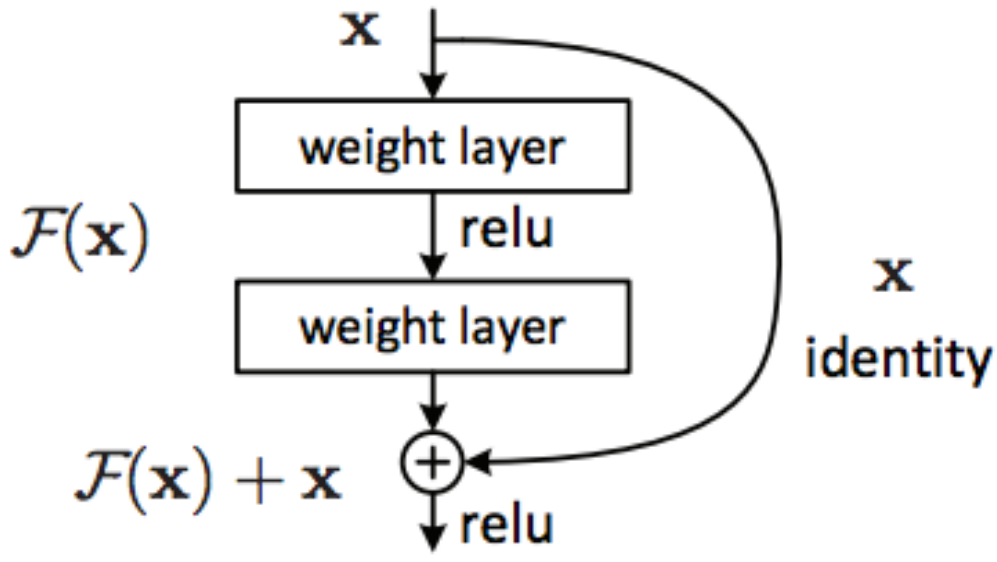
Xception and MobileNet

Depthwise separable convolutions have been made popular by their adoption in

- Xception
- MobileNet - a class of "light" models conceived to be deployed on mobile devices.

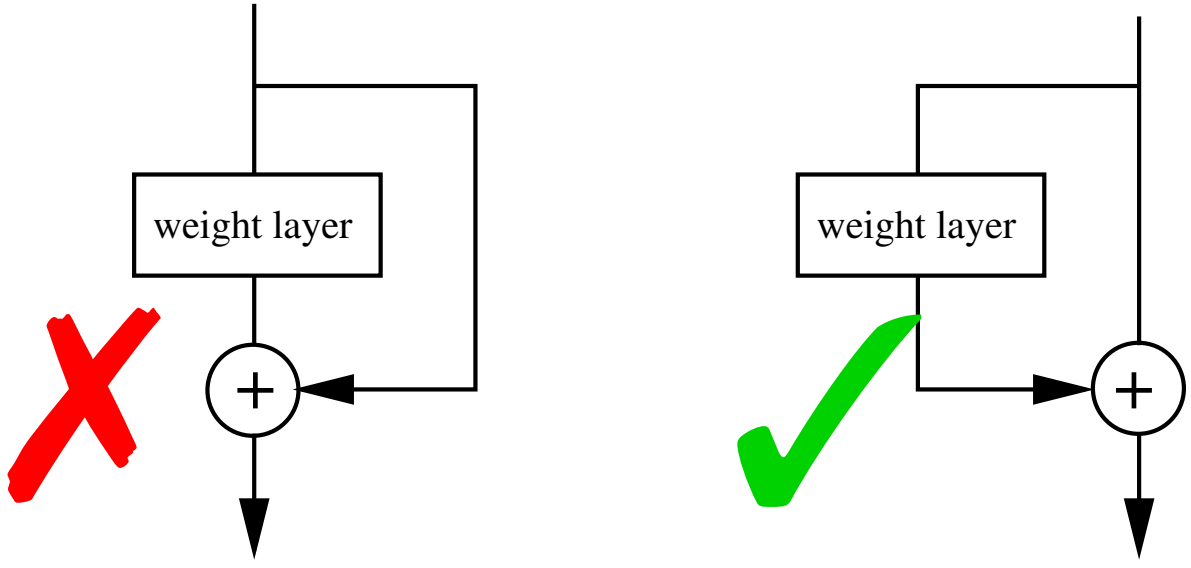
Residual Learning

Another recent topic is residual learning.

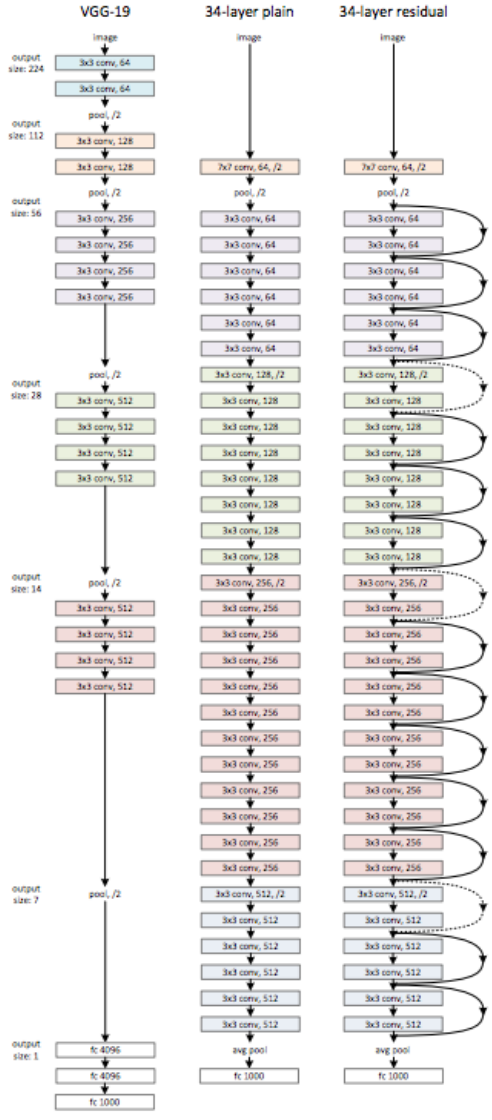


Instead of lerning a function $\mathcal{F}(x)$ you try to learn $\mathcal{F}(x) + x$.

The right intuition



Residual networks



you add a residual shortcut connection every 2-3 layers

Inception Resnet is an example of a such an architecture

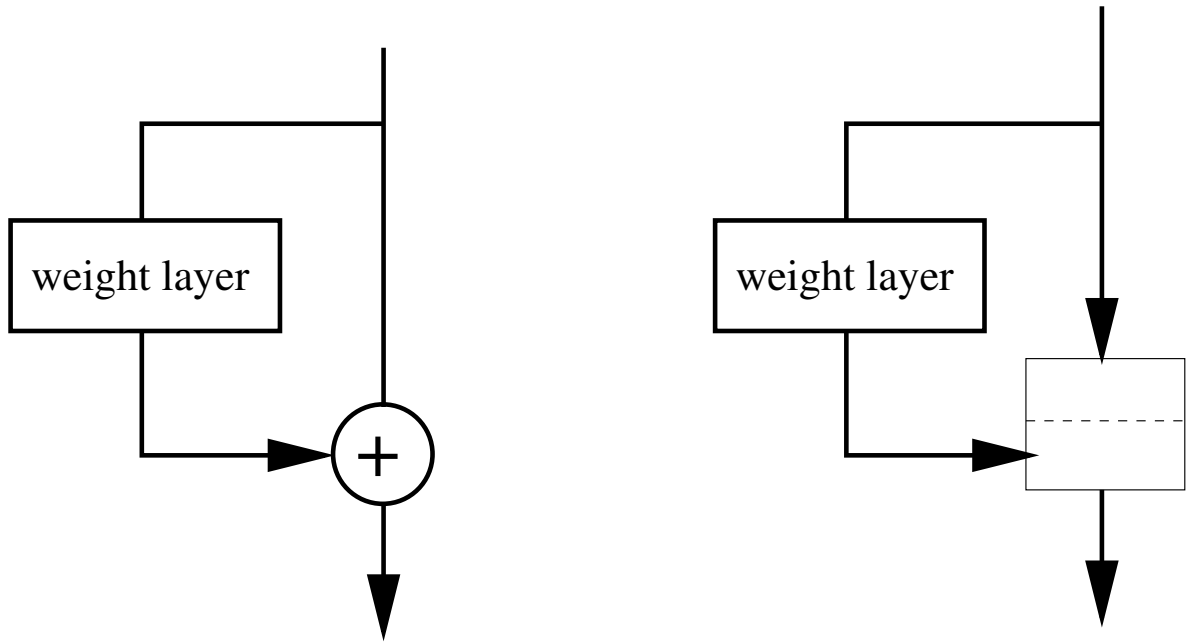
Why Residual Learning works?

Not well understood yet.

The usual explanation is that during back propagation, **the gradient at higher layers can easily pass to lower layers**, withouth being mediated by the weight layers, which may cause vanishing gradient or exploding gradient problem.

Sum or concatenation?

The "sum" operation can be interpreted in a liberal way.
A common variant consists in concatenating instead of adding (usually along the channel axis):



Efficient Net

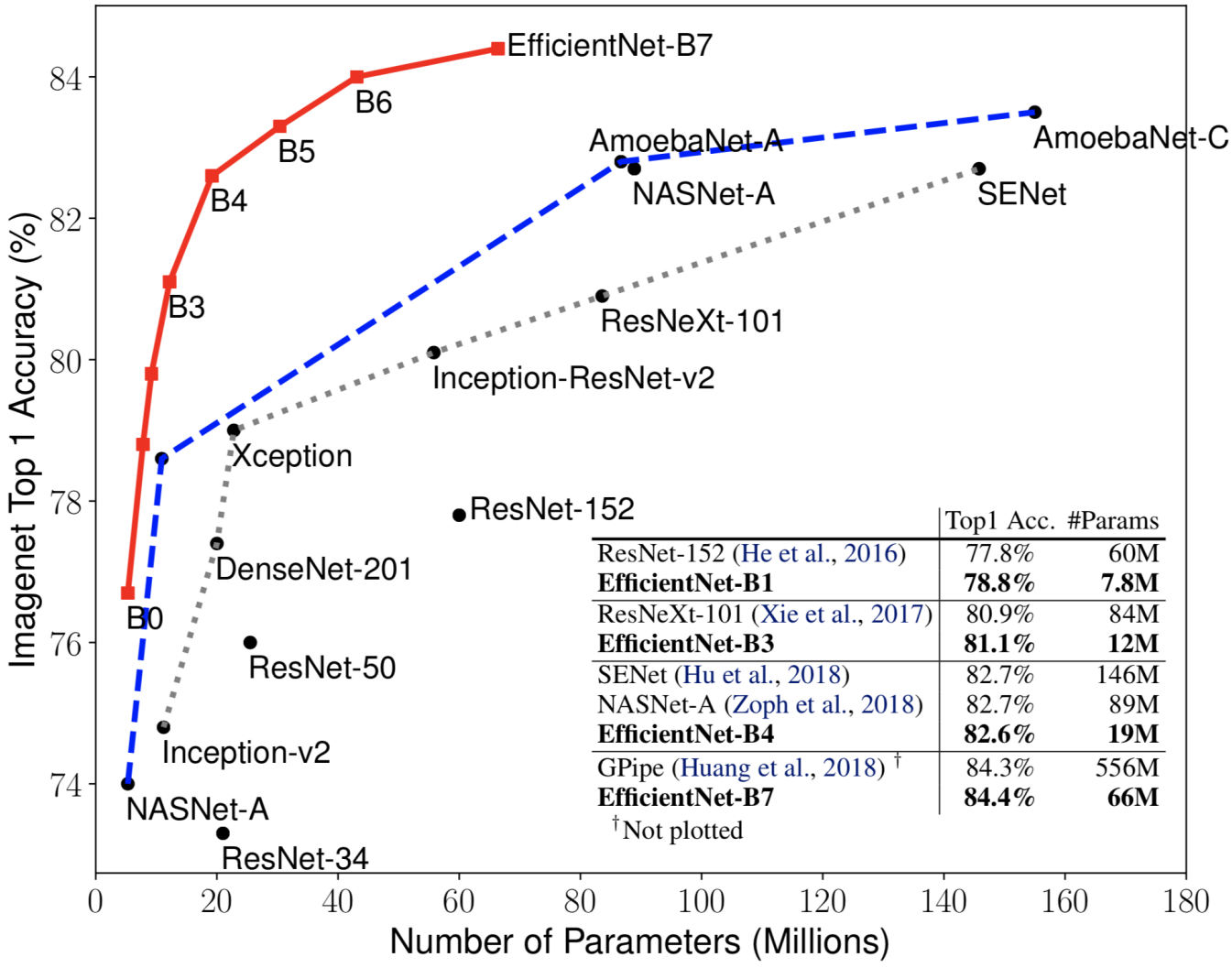
ConvNets essentially grow in three directions:

- **Layers**: the number of layers
- **Channels**: the number of channels for layers
- **Resolution**: the spatial width of layers

Is there a principled method to scale up ConvNets that can achieve better accuracy and efficiency?

Question addressed in EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

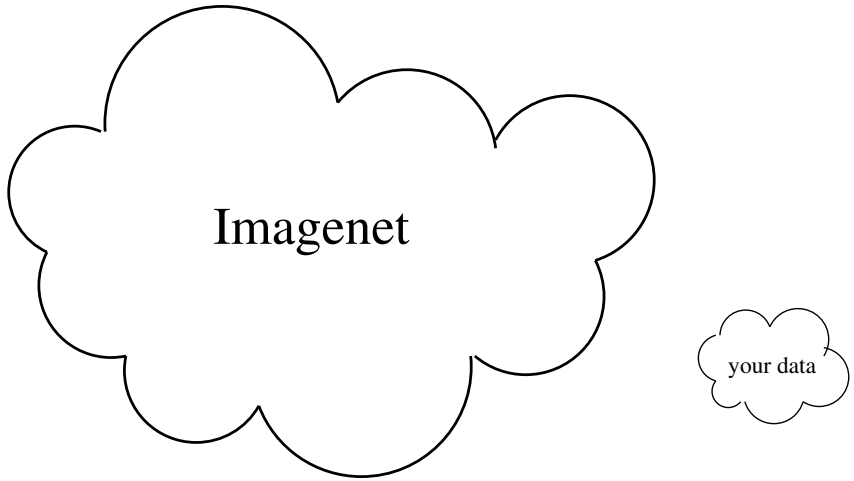
Efficient Net



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**78.8%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.1%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.6%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.4%**	**66M**

†Not plotted

Transfer Learning



Reusing Knowledge

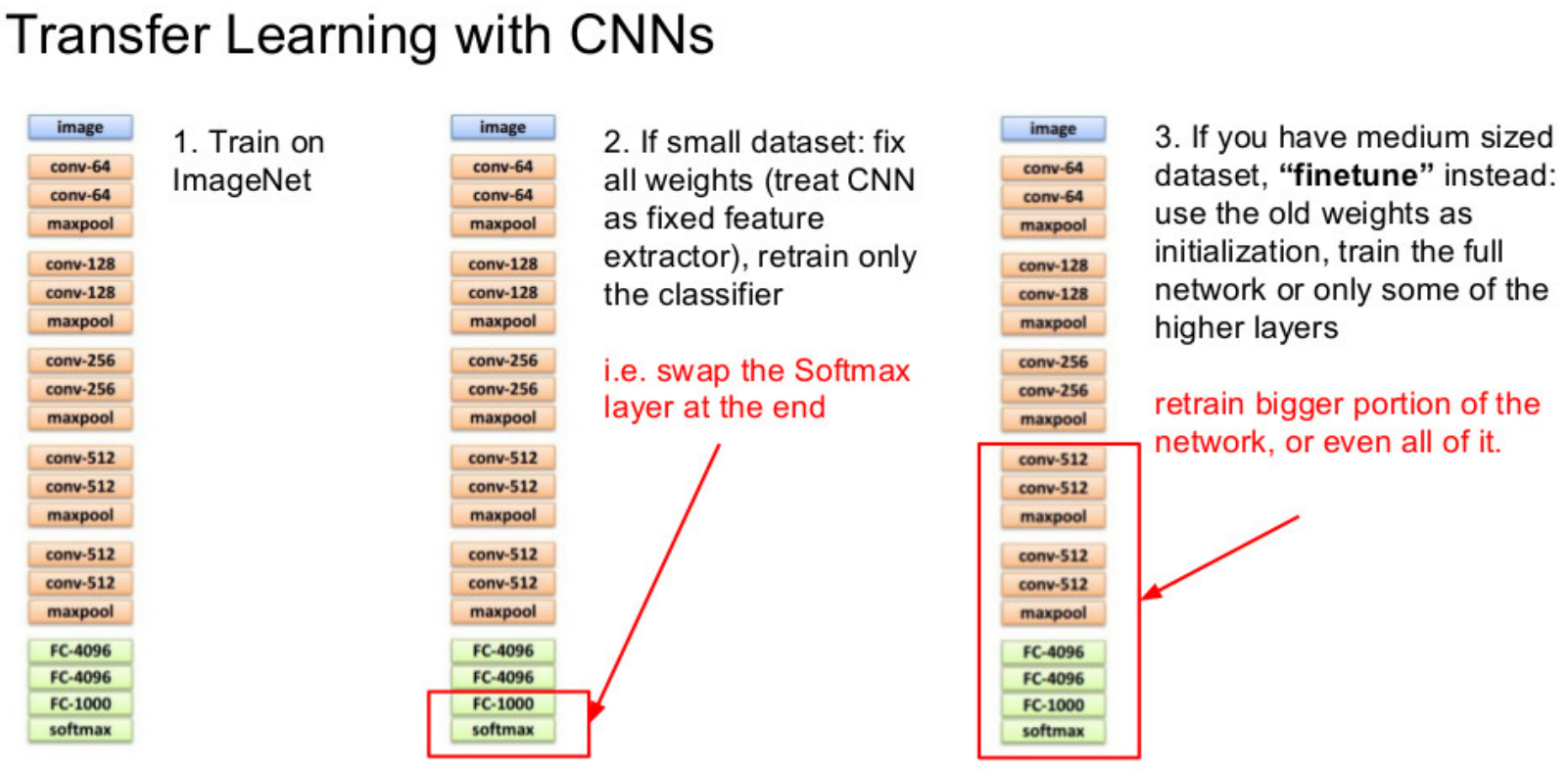
We learned that the first layers of convolutional networks for computer vision compute feature maps of the original image of growing complexity.

The filters that have been learned (in particular, the most primitive ones) are likely to be independent from the particular kind of images they have been trained on.

They have been trained on a huge amount of data and are probably very good.

It is a good idea to try to *reuse them* for other classification tasks.

Transfer Learning with CNNs



When Transfer Learning makes sense

transferring knowledge from problem A to problem B makes sense if

- the two problems have "similar" inputs
- we have much more training data for A than for B

What we may expect

Faster and more accurate training